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ABSTRACT

Relations among students' cognitive structures, instruction, and course achievement were studied for 102 undergraduates in three courses. An aim of the study was to integrate expert-novice research with investigations of cognitive-structure change. Experienced instructors identified concepts central to the different courses. Students were asked to cluster the items early in the courses and again at the courses' end, and these clusterings were compared to the groupings arranged by instructors. Multidimensional-scaling analysis was used to measure the cognitive structures of students in each course. The average difference of terms in a group from the group centroid, central term, was used as a measure of coherence. The increase in terms of coherence for one course (educational psychology) was close to significant; in another course (physics) the increase was significant, and in a third (women's studies), the increase was not significant. The prediction that students' cognitive structures become more coherent with instruction was supported, but the importance of other variables cannot be ignored. The difference in results across the disciplines is discussed. Eight figures and five tables present study data. (Contains 25 references.) (SLD)

USING MULTIDIMENSIONAL SCALING TO MEASURE CONCEPTUAL CHANGE

Dr. Ruth Streveler

Using Multidimensional Scaling to Measure Conceptual Change

Dr. Ruth Streveler[1]

Introduction

For over twenty years, researchers in cognitive and educational psychology have grappled with the problem of describing how cognitive structures change as an individual acquires knowledge in a domain. One approach to this question has compared the cognitive structures of experts and novices in various domains (McKeithen et al., 1981; Chi & Koeske, 1983; Gobbo & Chi, 1986; Chi, Hutchinson, & Robin, 1989). A second approach describes the differences in students' cognitive structures before and after instruction (Shavelson, 1972; Shavelson, 1974; Shavelson & Geeslin, 1975; Geeslin & Shavelson, 1975; Shavelson & Stanton, 1975; Champagne et al., 1981; Shavelson, 1985; Naveh-Benjamin, et al., 1986, 1989). The results from these two approaches should be complementary and findings of expert-novice studies should predict how students' cognitive structures will change. An aim of the present study is to integrate expert-novice research with investigations of cognitive structure changes in students. Specifically, this paper will investigate the relationships between students' cognitive structures, instruction and course achievement.

Methods

Participants

Participants in the study were undergraduates at a major research university who were enrolled in one of three courses: Educational Psychology (Psychological Foundations), Physics (College Physics), or Women's Studies (Introduction to Women's Studies). These courses were selected because they represented a range of disciplines, yet were all introductory in nature. Physics was the largest course by far, with an enrollment of 177 students. By contrast, 23 students were enrolled in Educational Psychology, and the Women's Studies course had an enrollment of 20

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students. The distribution of course grades was also quite different for the courses. Very few students received a grade of C or below in either the Educational Psychology or Women's Studies courses, however, almost 60% of the students in the Physics course received a grade of C or below.

Procedure

Prior to start of the semester, three experienced instructors from three different introductory courses (Physics, Educational Psychology and Women's Studies) were asked to select 30 terms they felt were central to their respective courses. Each course was visited at the beginning and end of the semester. During the pretest, students were given envelopes containing strips of paper listing each of the 30 important course terms and were asked to cluster the thirty terms in any manner they thought appropriate. About a week later, each instructor was asked to cluster terms and state why the concept in each group belonged together.

Posttests were administered within the last two weeks of instruction. Using the same terms from the pretest, students were asked to cluster terms appropriately. Students were also asked for permission to use their course grades. Instructors were also be asked to cluster the terms at the end of the semester. All three instructors chose to do the final clustering at the same time the students were clustering terms.

Only data from the students in the courses who completed both the pretest and posttest were used in this study. Thus the actual number of participants was 14 Educational Psychology students, 74 Physics students, and 14 Women's Studies students, or a grand total of 102 student participants.

Data analysis

Multidimensional scaling analysis was used to measure the cognitive structures of students in each of the three courses before and after instruction. The overlap of both student pretest and posttest clusters in each course was determined using the

program PEROVER (Dunn-Rankin, 1983). The resultant percent overlap matrices were then analyzed using the SAS program ALSCAL (Young & Lewyckyj, 1979). Levels of stress for 2-dimensional and 3-dimensional solutions were determined for each of the three classes. It was determined that 3-dimensional solutions were appropriate.

The multidimensional scaling solutions generated by the students clusters were next compared to the way in which the instructor clustered the terms. This comparison was accomplished by assigning terms to groups according to the instructors' clusters and comparing how the students' pretest and posttest groups changed relative to the instructors' groups.

The center or centroid of the set of terms in each of the instructor's groups was then calculated by determining the average of the x, y, and z coordinates of terms within that group. The distance of each term in the group from the group centroid was determined geometrically using the formula:

Distance of point from centroid =

square root$((x_1-x_2)^2 + (y_1-y_2)^2 + (z_1-z_2)^2)$

where x_2, y_2, z_2 are the coordinates of the centroid of the group, and x_1, y_1, z_1 are the coordinates of the term whose distance is being determined.

The average distance of each term in a group from the group centroid was determined for all groups. The average distance wias used as a measure of the coherence of a cluster. The term coherence refers to the strength of with-in group links versus between-group links (Chi & Koeske, 1983).

A binomial test was performed to compare the pretest and posttest distances to see if the posttest groups are significantly more coherent than the pretest groups. In this sense, the pairs of pretest and posttest average distances for each of the three courses are then viewed as being a series of trials (with each

cluster being a separate, independent trial) and with the situation "pretest average distance larger than the posttest average distance" considered a success and "pretest average distance smaller than the posttest average distance," a failure. One assumes that, by chance, the probability of the pretest average distance being larger than the posttest average distance is .5.

In order to test the prediction that students with high course grades would cluster the terms more coherently than students with low course grades, the grades students received in the three courses were needed. Instructors agreed to provide both the overall grade distribution, and the grades of individual students who had given their permission for their course grade to be shared. Only data from students who took both the pretest and the posttest <u>and</u> who agreed to have their course grade shared could be used. With those two limitations accounted for, the actual number of students eligible to participate was eight in Educational Psychology, sixty-two in physics, and ten in Women's Studies. Given this situation,the judgment was made only to use the data from Physics, which was deemed to be the only one of the three courses with a large enough grade distribution to warrant analysis.

Subsets of the Physics posttest data were analyzed and compared. Data for students receiving grades of either A or B were combined, as were the data for students receiving grades of D or F. These subsets of data were analyzed using PEROVER (Dunn-Rankin, 1983) and ALSCAL (Young & Lewyckyj, 1979). The terms were assigned to groups according to the instructor's groupings.

Results

Since instructors clustered terms at the beginning and end of the semester, it was necessary to look at both the pretest and posttest clustering of terms by each instructor to determine which of the instructor grouping (pretest or posttest) should be used as

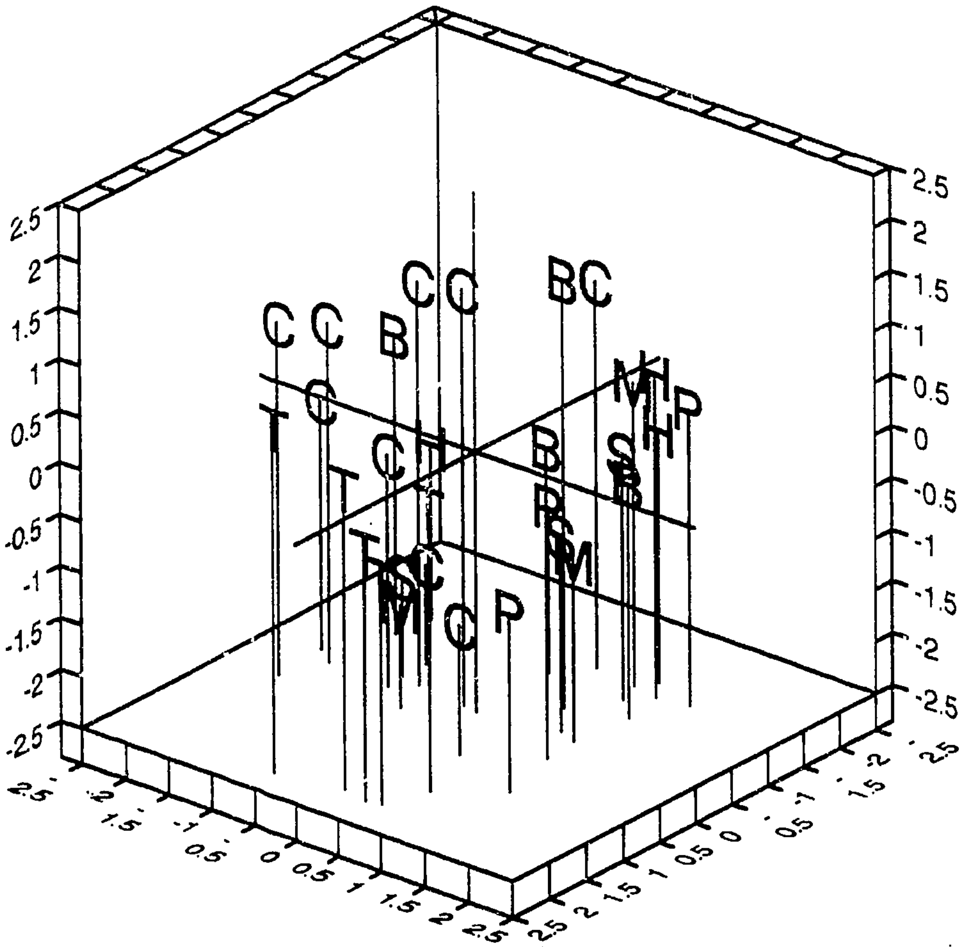
a criterion for assigning terms to groups. (For a listing of instructor groupings see Streveler, 1993). The number of terms changed from pretest to posttest by the instructor in each of the three course was quite varied. The Educational Psychology instructor made no changes. The Physics instructor changed 7 of 30 terms (or 23.3% of terms) from pretest to posttest while the Women's Studies instructor changed 13 of 30 terms (43.3%) from pretest to posttest. Due to the variability in the Physics and Women's Studies instructors' responses, a judgment was made about which set of instructor clusters (pretest groups or posttest groups) to use as a criterion for comparison with student clusters. Because the instructors' posttest clusters were completed at the end of the semester, it was assumed that the posttest clusters would be a more valid measure of how the course terms related at the completion of the course.

Plots of the pretest and posttest clustering of terms by students for each course are found in Figures 1 through 6 which can be used to visually assess the coherence of student clusters with regards to the instructors' groupings. This can be seen most dramatically in Figures 1 and 2 where the terms the instructor categorized as "psychometric terms" become much more closely clustered from the pretest to the posttest. Since the visual assessment of plots is much more difficult when a dramatic shift is not apparent, a quantitative measure of coherence was also calculated. Coherence of groups was determined by calculating the average distance of points in a group from the group centroid. The results are summarized in Tables 1, 2 and 3.

The average distance of terms from the group centroid is smaller in the posttest than in the pretest for most of the groups. Because the normality of the measure of coherence could not be assured, nonparametric tests of significance were judged to be more appropriate in this case. Thus a binomial test was used to test the significance of the difference in the average distance of groups from pretest to posttest.

Figure 1.

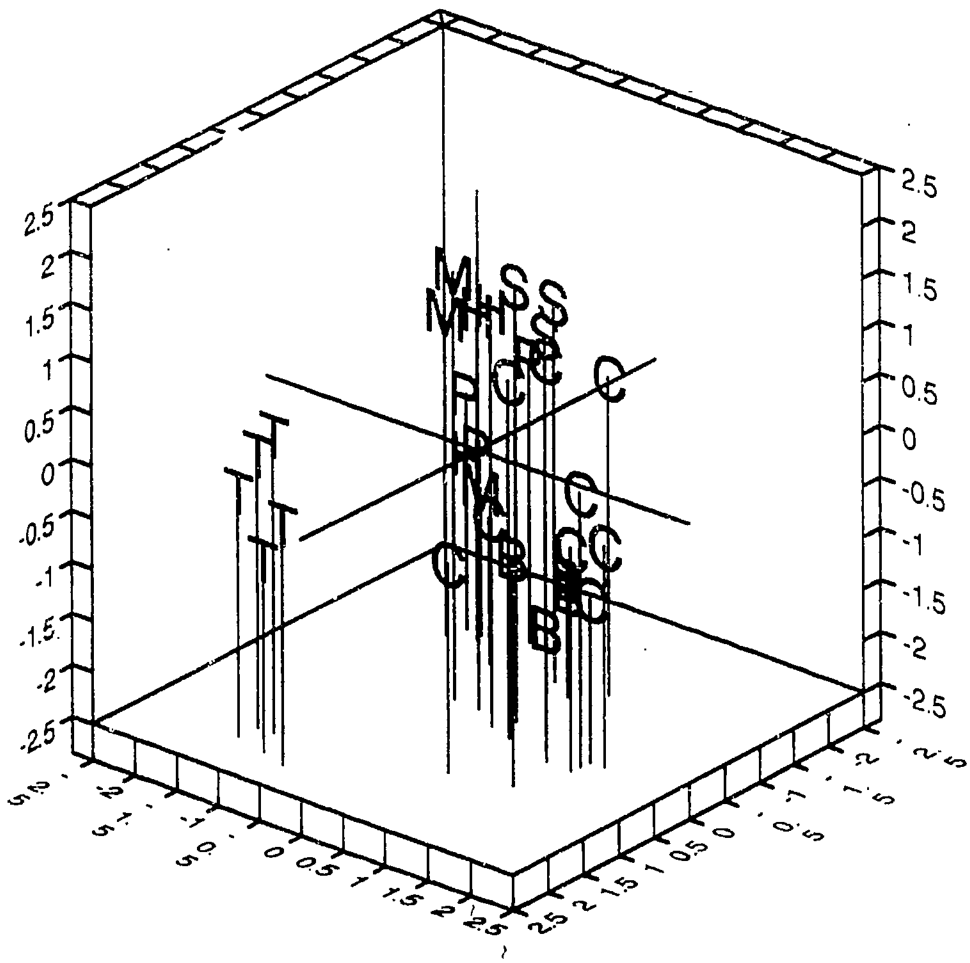
Pretest of students' clustering of important course terms in Educational Psychology



Legend

C = Cognitive terms	(9 terms)
T = Psychometric terms	(5 terms)
B = Behaviorist terms	(4 terms)
P = Psychosocial terms	(3 terms)
H = Humanistic terms	(3 terms)
S = Social learning terms	(3 terms)
M = Motivation terms	(3 terms)

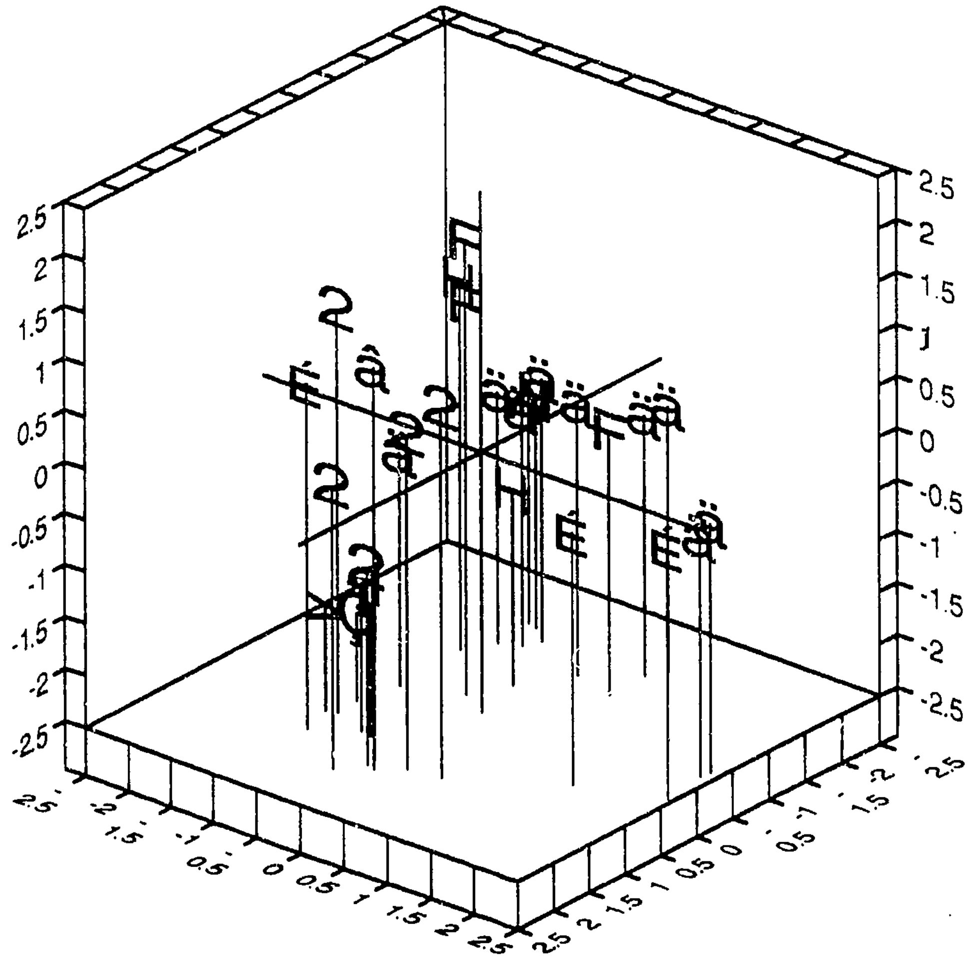
Figure 2.
Posttest of students clustering of important
course terms in Educational Psychology



Legend

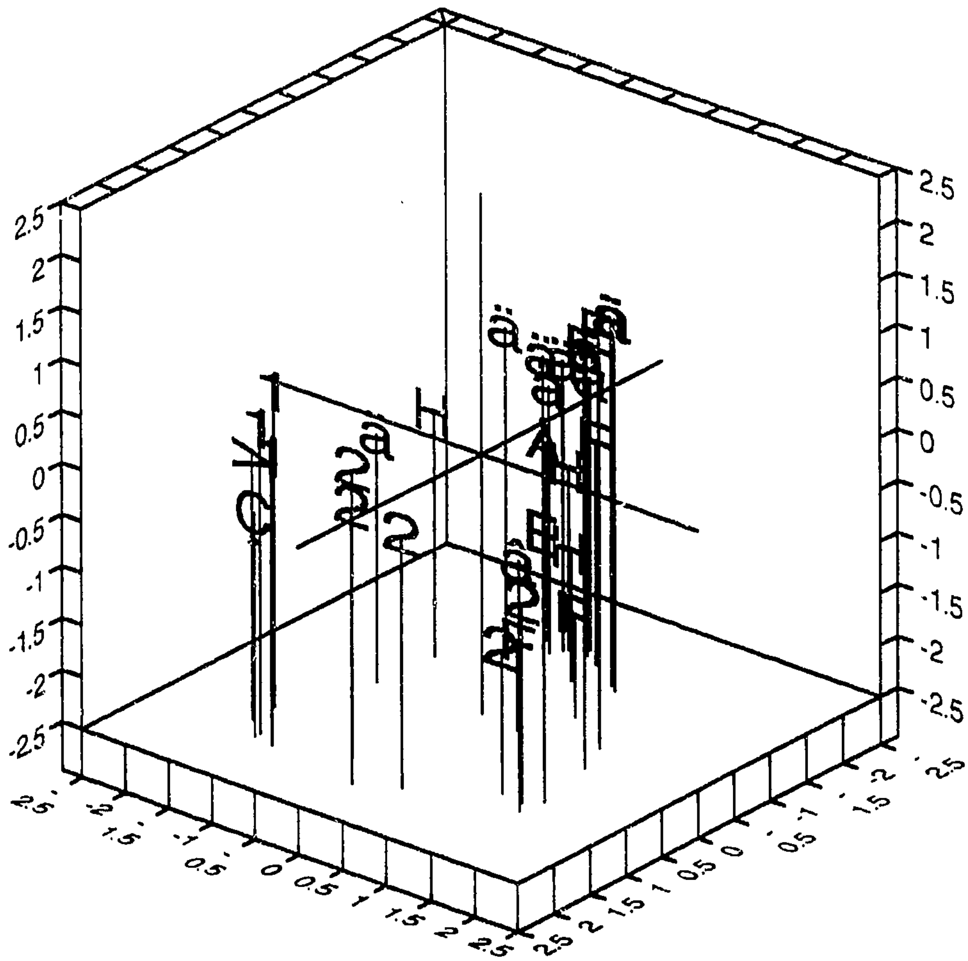
C = Cognitive terms (9 terms)
T = Psychometric terms (5 terms)
B = Behaviorist terms (4 terms)
P = Psychosocial terms (3 terms)
H = Humanistic terms (3 terms)
S = Social learning terms (3 terms)
M = Motivation terms (3 terms)

Figure 3.
Pretest of students' clustering of important course terms in Physics.



Legend
a = Newton's Second Law of Motion (9 terms)
1 = Light (3 terms)
H = Relates to Momentum (3 terms)
F = Energy (3 terms)
2 = Second Law of Thermodynamics (5 terms)
E = Fluids (3 terms)
C = Electromagnetic waves (1 term)
Å = Angular Momentum (1 term)
> = Matter Waves (1 term)
å = Ideal Gas Laws (1 term)

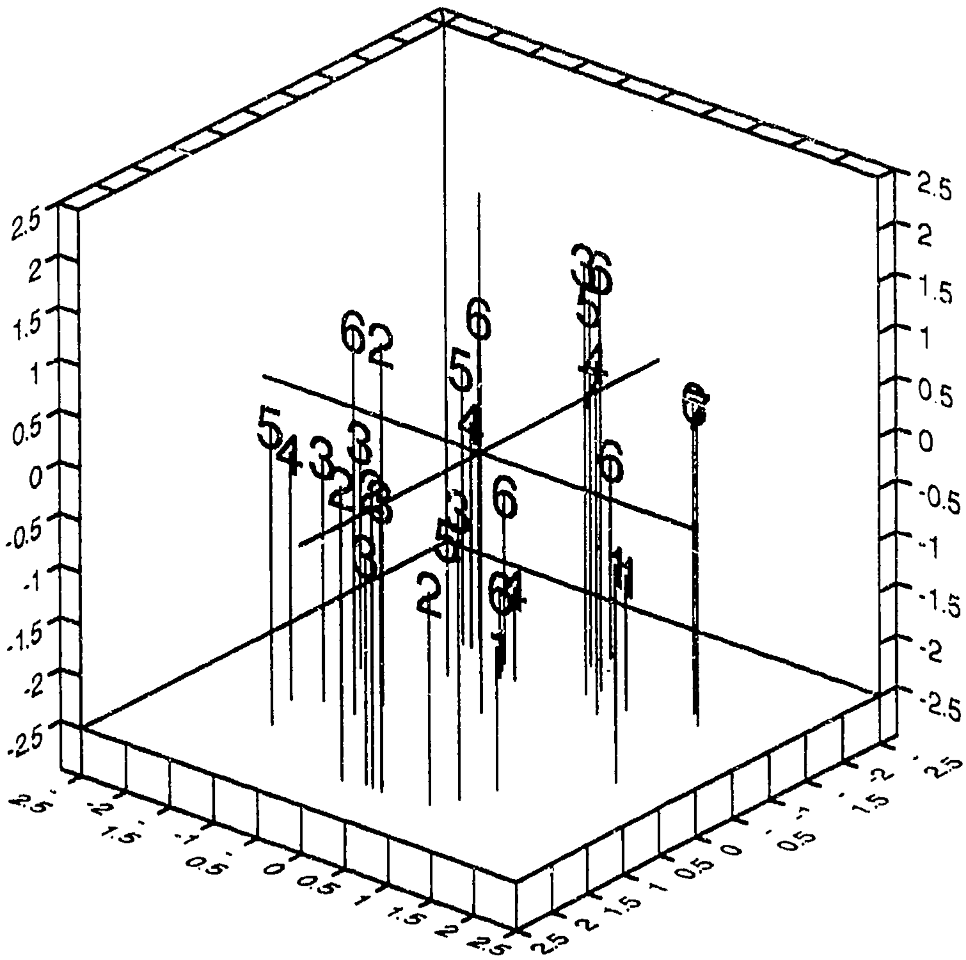
Figure 4.
Posttest of students' clustering of important course terms in Physics.



Legend

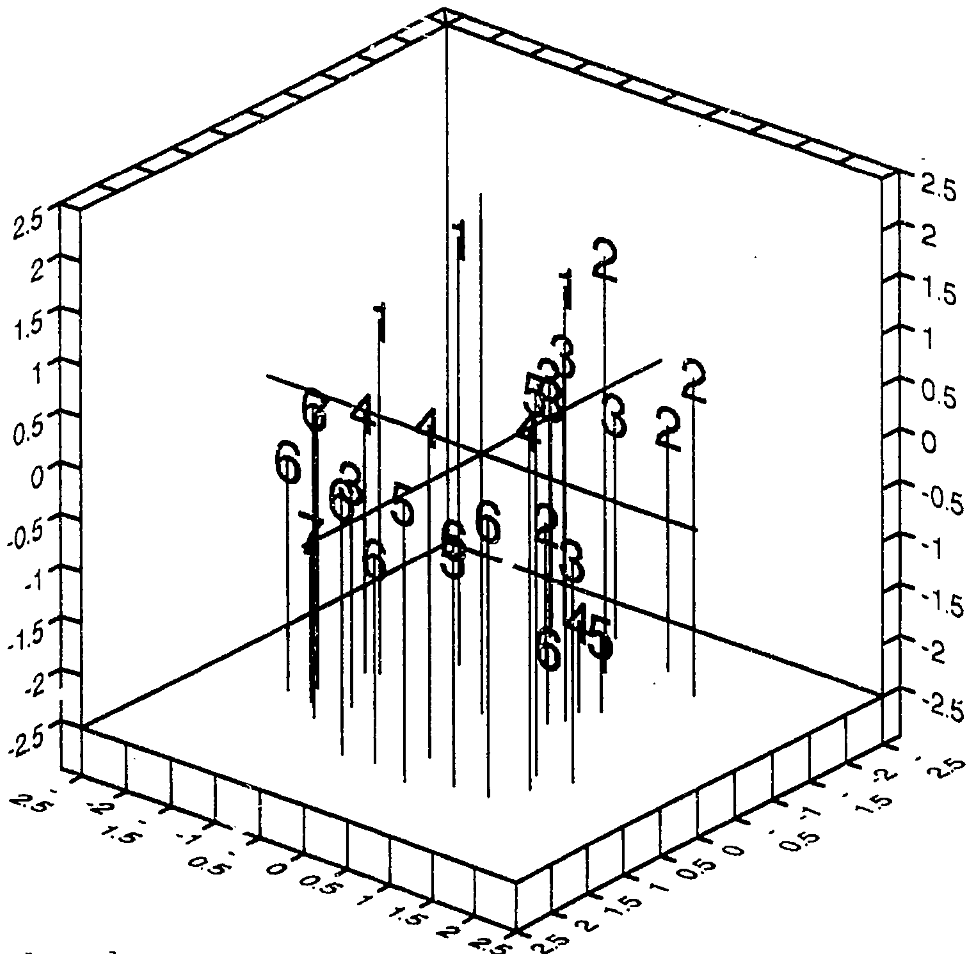
a = Newton's Second Law of Motion (9 terms)
1 = Light (3 terms)
H = Relates to Momentum (3 terms)
F = Energy (3 terms)
2 = Second Law of Thermodynamics (5 terms)
E = Fluids (3 terms)
C = Electromagnetic waves (1 term)
Å = Angular Momentum (1 term)
> = Matter Waves (1 term)
å = Ideal Gas Laws (1 term)

Figure 5.
Pretest of students' clustering of important course terms in Women's Studies.



Legend
1 = Gr. 1: Systems of power in a culture of dominance (3 terms)
2 = Gr. 2: Challenges to Group 1 (4 terms)
3 = Gr. 3: Produced within the social conditions of Group1 (6 terms)
4 = Gr. 4: Strategies of those forms of dominance in Group1 (4 terms)
5 = Gr. 5: Produced through Group2 (4 terms)
6 = Gr. 6: Strategies of feminism (7 terms)
7 = Gr. 7: Contended for by both Group 1 and Gr2, but mean very different things by both (2 terms)

Figure 6.
Posttest of students' clustering of important course terms in Women's Studies.



Legend
1 = Gr. 1: Systems of power in a culture of dominance
(3 terms)
2 = Gr. 2: Challenges to Group 1
(4 terms)
3 = Gr. 3: Produced within the social conditions of Group1
(6 terms)
4 = Gr. 4: Strategies of those forms of dominance in Group1
(4 terms)
5 = Gr. 5: Produced through Group2
(4 terms)
6 = Gr. 6: Strategies of feminism
(7 terms)
7 = Gr. 7: Contended for by both Group 1 and Gr2, but mean very different things by both
(2 terms)

Table 1
Average distances of terms from the group centroid for the pretest and posttest in Educational Psychology.

Group 1: Cognitive terms
(number of terms in group = 9)
Average distance from centroid of group

Pretest	1.387
Posttest	1.126

Group 2: Psychometric terms
(number of terms in group = 5)
Average distance from centroid of group

Pretest	0.586
Posttest	0.456

Group 3: Behaviorist terms
(number of terms in group = 4)
Average distance from centroid of group

Pretest	1.337
Posttest	0.936

Group 4: Psychosocial terms
(number of terms in group = 3)
Average distance from centroid of group

Pretest	1.349
Posttest	0.718

Group 5: Humanistic terms
(number of terms in group = 3)
Average distance from centroid of group

Pretest	1.241
Posttest	1.304

Group 6: Social learning terms
(number of terms in group = 3)
Average distance from centroid of group

Pretest	1.063
Posttest	0.676

Group 7: Motivation theory terms
(number of terms in group = 3)
Average distance from centroid of group

Pretest	1.215
Posttest	1.199

Table 2

Average distances of terms from the group centroid for the pretest and posttest in Physics.

Group 1: Newton's Law of Motion
(number of terms in group = 9)
Average distance from centroid of group
Pretest 1.205
Posttest 0.660

Group 2: Light
(number of terms in group = 3)
Average distance from centroid of group
Pretest 0.425
Posttest 0.319

Group 3: Relates to momentum
(number of terms in group = 3)
Average distance from centroid of group
Pretest 0.897
Posttest 0.740

Group 4: Energy
(number of terms in group = 3)
Average distance from centroid of group
Pretest 0.887
Posttest 0.821

Group 5: Second Law of Thermodynamics
(number of terms in group = 5)
Average distance from centroid of group
Pretest 0.854
Posttest 0.829

Group 6: Fluids
Average distance from centroid of group
(number of terms in group = 3)
Pretest 1.434
Posttest 0.796

Group 7: Electromagnetic waves
(number of terms in group = 1)

Group 8: Angular momentum
Average distance from centroid of group
(number of terms in group = 1)

Group 9: Matter waves
(number of terms in group = 1)

Group 10: Ideal Gas Laws
(number of terms in group = 1)

Table 3
Average distances of terms from the group centroid for the pretest and posttest in Women's Studies.

Group 1: Systems of power in a culture of dominance
(number of terms in group = 3)
Average distance from centroid of group

Pretest	1.055
Posttest	0.927

Group 2: These are challenges to Group 1
(number of terms in group = 4)
Average distance from centroid of group

Pretest	0.908
Posttest	1.074

Group 3: These are produced within the social conditions of Group 1
(number of terms in group = 6)
Average distance from centroid of group

Pretest	1.450
Posttest	1.297

Group 4: These are strategies of those forms of dominance in Group 1
(number of terms in group = 4)
Average distance from centroid of group

Pretest	1.389
Posttest	1.519

Group 5: These are produced through Group 2
(number of terms in group = 4)
Average distance from centroid of group

Pretest	1.359
Posttest	1.279

Group 6: Strategies of feminism
(number of terms in group = 7)
Average distance from centroid of group

Pretest	1.476
Posttest	1.182

Group 7: The are contended for by both Groups 1 and 2, but mean very different things by both.
(number of terms in group = 2)
Average distance from centroid of group

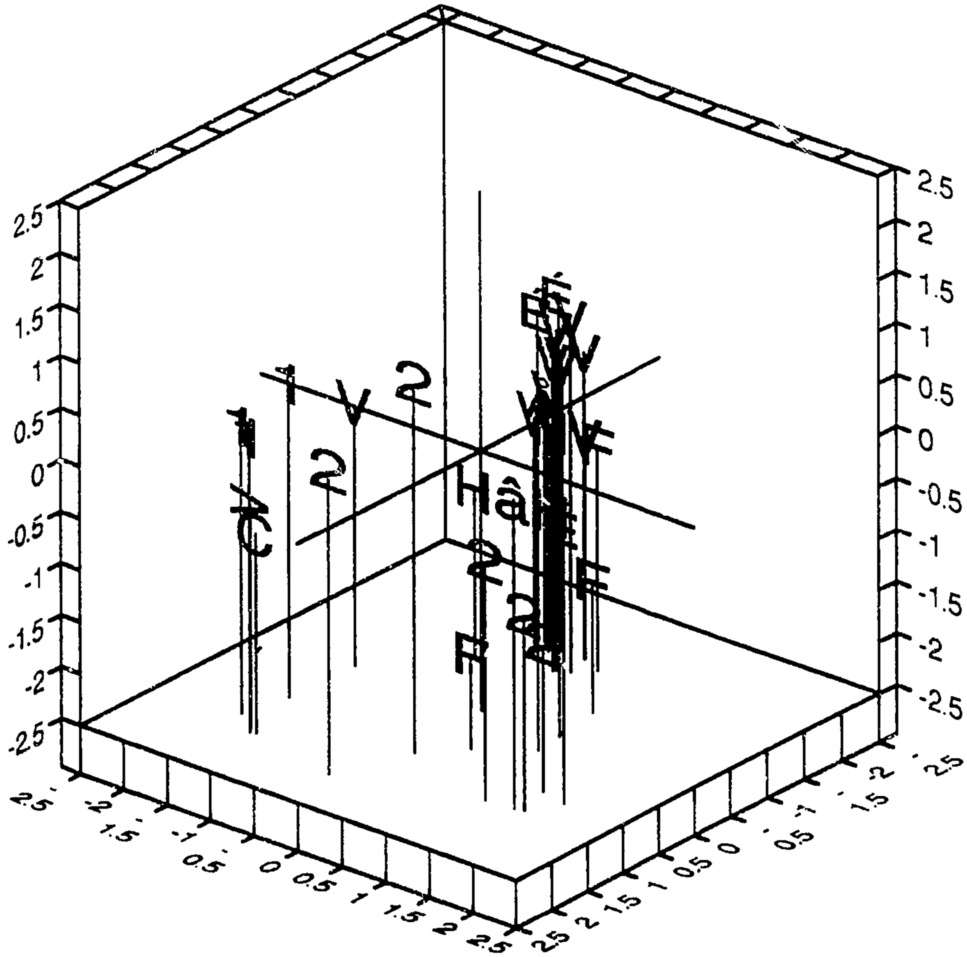
Pretest	0.913
Posttest	0.547

Using the binomial test we can calculate the probability of the pretest distances being larger than the posttest distance by chance alone. At the p = .05 level of significance, the results of Physics are considered significant (B = .016), and the results of Educational Psychology closely approach significance (B = .055). However, the binomial probability for the Women's Studies course is not significant at the p = .05 level (B = .164). If the results of all three courses are combined the results are highly statistically significant (B = .001).

The clustering of a combined group of A and B students and a combined group of D and F students were analyzed using PEROVER and ALSCAL and are plotted in Figures 7 and 8. The average distance of terms in each group from the centroid of that group are listed in Table 5.

One could predict that the better performing students (here represented by students receiving grades of A and B) would have more coherent clusters than students who do not perform well in the course (represented by students receiving grades of D and F). The binomial test was again used in this comparison. The results of the binomial test were in the predicted direction but failed to reach statistical significance (B = .093). Therefore, the prediction was not supported.

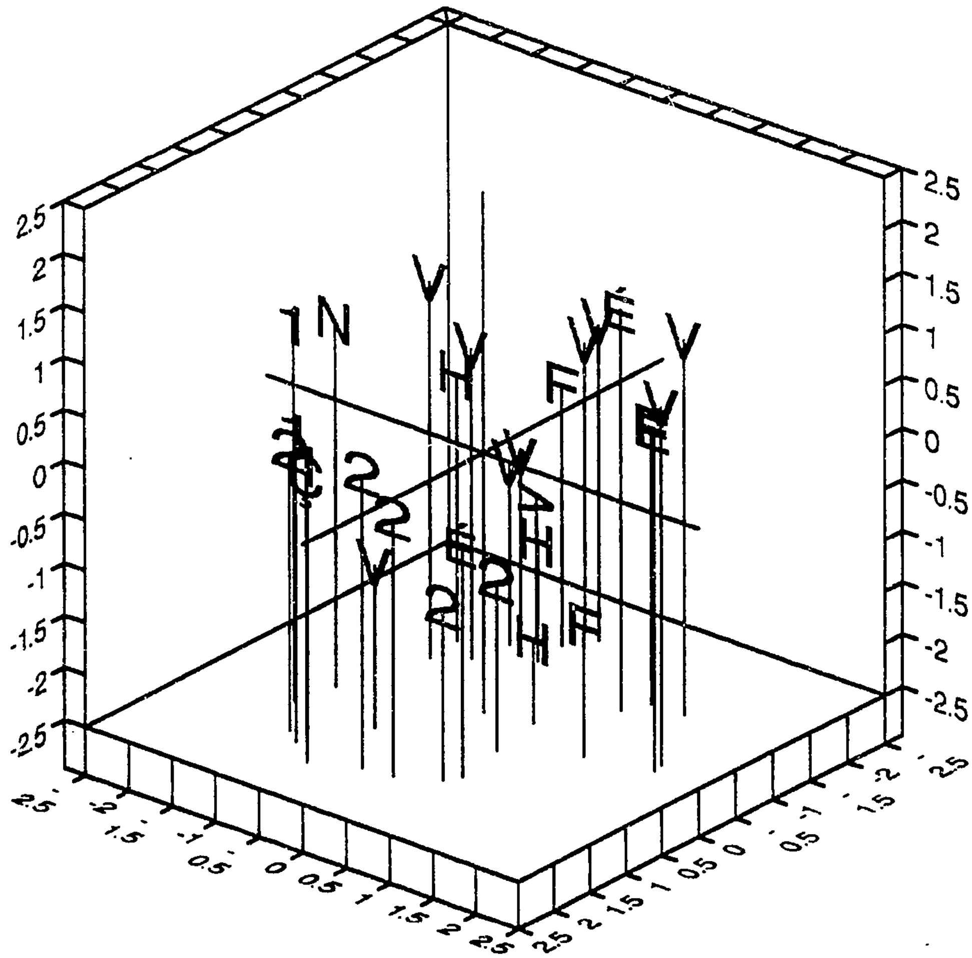
Figure 7.
Posttest of A and B students' clustering of important course terms in Physics.



Legend

a = Newton's Second Law of Motion (9 terms)
1 = Light (3 terms)
H = Relates to Momentum (3 terms)
F = Energy (3 terms)
2 = Second Law of Thermodynamics (5 terms)
E = Fluids (3 terms)
C = Electromagnetic waves (1 term)
Å = Angular Momentum (1 term)
> = Matter Waves (1 term)
å = Ideal Gas Laws (1 term)

Figure 8.
Posttest of D and F students' clustering of important course terms in Physics.



Legend
a = Newton's Second Law of Motion (9 terms)
1 = Light (3 terms)
H = Relates to Momentum (3 terms)
F = Energy (3 terms)
2 = Second Law of Thermodynamics (5 terms)
E = Fluids (3 terms)
C = Electromagnetic waves (1 term)
Å = Angular Momentum (1 term)
> = Matter Waves (1 term)
å = Ideal Gas Laws (1 term)

Table: 5

Average distances of terms from the group centroid for the posttest in Physics: A and B students and D and F students.

Group 1: Newton's Law of Motion
(number of terms in group = 9)
Average distance from centroid of group
A and B students 0.621
D and F students 1.404

Group 2: Light
(number of terms in group = 3)
Average distance from centroid of group
A and B students 0.351
D and F students 0.552

Group 3: Relates to momentum
(number of terms in group = 3)
Average distance from centroid of group
A and B students 0.459
D and F students 1.037

Group 4: Energy
(number of terms in group = 3)
Average distance from centroid of group
A and B students 0.922
D and F students 1.139

Group 5: 2nd Law of Thermodynamics
(number of terms in group = 5)
Average distance from centroid of group
A and B students 1.050
D and F students 0.842

Group 6: Fluids
(number of terms in group = 3)
Average distance from centroid of group
A and B students 0.904
D and F students 1.152

Group 7: Electromagnetic waves
(number of terms in group = 1)

Group 8: Angular momentum
(number of terms in group = 1)

Group 9: Matter waves
(number of terms in group = 1)

Group 10: Ideal Gas Laws
(number of terms in group = 1)

Discussion

Students' cognitive structures and instruction

If students move closer to being experts after instruction, then one could expect that the cognitive structures of students will be more like the cognitive structures of experts after instruction. If cognitive structures of experts are more coherent than the cognitive structures of novices, then one could predict that the inferred cognitive structures of students after instruction are more coherent than those inferred before instruction.

The average distance of terms in a group from the group centroid was used as a measure of coherence. Using the binomial probability with a $p = .05$ level of significance, the increase in coherence of terms in the Educational Psychology course was very close to significance, the increase in coherence of terms in the Physics course was significant, and in the Women's Studies course results, the the increase in coherence of terms would not be considered significant.

What accounts for these differences between courses? One explanation might lay in the structure of the three different disciplines represented. There is some evidence that the content of some disciplines is more hierarchically structured than the content of other disciplines. For example, Donald (1982, 1983, 1986) found that some sciences, like physics, were much more hierarchically structured than some humanities, for example, history. Looking at the three domains represented by the courses in this study, one could argue that Physics is the most "structured," and Women's Studies the least structured. A comparison of the individual instructor's variability in clustering is somewhat compatible with this idea. One would expect least variability in the Physics instructor's pre- and posttest clusterings and the most variability in the Women's Studies instructor's clusterings. The Women's Studies instructor

(with 43% of terms changed) was the most variable, however, the Educational Psychology instructor (with no terms changed) was the least variable. It is reasonable to expect that personality differences also may come into play here and may have accounted for this result. It should also be noted that the Educational Psychology instructor was familiar with the clustering method and therefore may have been more mindful of which terms were placed into clusters than the other two instructors, who had never used the technique.

In explaining the results obtained in this study it is also useful to look more closely at the groups where the posttest average distance was NOT smaller than the pretest average distance. (See Streveler, 1993 for specifics.)

In summary, although the prediction that students' cognitive structures become more coherent after instruction is supported, other influences such as structural relatedness of terms, student familiarity with terms, and the variability of the instructors' cognitive structure may also play a part in determining students' cognitive structures.

Students' cognitive structures and course achievement

Do students who receive high course grades have more coherent cognitive structures than students who receive low course grades? There is prior evidence that students with higher course grades have cognitive structures closer to that of the instructor than students with lower course grades (Naveh-Benjamin et al., 1986, 1989).

In Physics, five of six groups of terms did have a smaller posttest average distance by students who received grades of A or B, compared with students who received grades of D or F. The binomial test of these results ($\underline{B}$ = .094) does not support the prediction that students with higher final course grades have a more coherent cognitive structure than students who receive low

final course grades. However, because of the low number of groups, only a result where all six of the groups of terms have a smaller average distance would be significant according to the binomial test.

It should also be noted that a subset of students were used in this study. Thirty-one of a total of sixty-one (or about 50.8%) of students receiving a final course grade of A or B in Physics were included in this portion of the study, while only sixteen of seventy-eight (or 20.5%) of student receiving an grade of D or F were included. Clearly the students with lower grades are underrepresented in the sample, primarily due to the fact that many more students who received low final grades were not present at the posttest compared with those students receiving high grades. Students who received a low course grade and who stopped coming to class might be expected to be even more different from A or B students than the D and F students who diligently kept trying to do the course work.

Even with these caveats in mind, it is interesting to note that in only one group was the average distance of terms from the group centroid smaller for D and F students, than for A and B students. This group was labeled "Second Law of Thermodynamics" by the instructor, and consisted of five terms, two of which were clustered differently by the Physics instructor in the pretest and posttest. In no other group of Physics terms was the instructor variability this high. If, as Nevah-Benjamin et al. (1986, 1989) suggest, student with higher grades have cognitive structures that are more similar to the instructor than lower achieving students, then it is possible that the ambiguity in the instructors' structure is reflected in the higher achieving students' cognitive structures. This may have contributed to a more diffuse clustering of this one group of terms.

In summary, although the within group coherence of groups was not statistically significantly different at the $p = .05$ level,

the results are encouraging enough to invite further study of student cognitive structure and course achievement with a larger sample.

Discussion of results across disciplines

It is interesting to note that the results obtained from the Women's Studies students were consistently set apart from the results for Educational Psychology and Physics students. The Women's Studies students' cognitive structures were in least agreement with the cognitive structure of their instructor and the Women's Studies instructor exhibited the most variability of clustering of terms from pretest to posttest.

Why should the Women's Studies course be so consistently different from the other courses? An attempt to explain these differences was made earlier, based on the idea of ill-structured and well-structured domains. However, a discussion with the Women's Studies instructor about the aim of her course revealed a possible explanation which goes beyond the idea of a domain being ill-structured. The Women's Studies instructor's goal is to assist her students in becoming unsettled in their thinking and deconstructing certain ingrained concepts. In this kind of course, relationships are deliberately broken down by the instructor in the educational process. The instructor is deconstructing a students' cognitive structures rather than trying to impose a organized existing structure. A similar approach might be likely in disciplines like philosophy (Phenix, 1964).

Thus it is possible that not all disciplines strive to be solidly structured and hierarchically organized. Some disciplines may have as a goal to break down students' cognitive structures, so that they can be rebuilt without the restrictions of old prejudices and perceptions.

It is intriguing to speculate that the results of this study may have been documenting the deconstruction of students cognitive

structures. If this is the case, then the assumption that students in a domain are more similar to experts in that domain after instruction than they are prior to instruction may not hold in all cases. It is possible that in some domains the intent of instruction is to disrupt current student thinking about some topics. Here, the instructor may wish students to vary their thinking from those of experts. The method of studying students' cognitive structures outlined in this study may be able to document cases when students' thinking (i. e., inferred cognitive structures) become more similar to the instructor's as well as when, hopefully by the intent of the instructor, they become less similar.

Implications for Education

Using the method outlined in this study, a plot of how students view the relationship between important course terms can be generated and presented to a course instructor. The instructor can view the plot to determine how closely the students' perceptions of relationships between terms matches the instructor's own perception. If students' groups are not consistent with the instructor's groupings, this may be a sign that the students are confused about the relationships involved. The instructor could then adjust the curriculum to reiterate these topics, perhaps stressing relationships that exist between concepts.

Close analysis of the plot of terms could also help the instructor pinpoint student misconceptions. For example, Streveler and Bail (1992) found that students in a graduate Educational Psychology course persistently grouped the term "vicarious reinforcement" with other terms containing the word "reinforcement" such as "positive reinforcer," "negative reinforcer," and "intermittent reinforcement".

The student placement of "vicarious reinforcement" differed from the instructor's clustering of the term. The instructor

grouped "vicarious reinforcement" with other terms related to observational learning theory, while "negative reinforcer," "positive reinforcer," and "intermittent reinforcement" were grouped by the instructor with terms relating to behaviorism. Thus the students' persistent placement, even at the end of the semester, of the term "vicarious reinforcement" with behaviorism-related terms could be seen as a misconception on the part of the students. Students might, for example, believe that because "vicarious reinforcement" is so structurally similar to other behaviorism terms that it, too, refers to behaviorism. It should be noted that students were able to place other semantically related terms into groups on the basis of meaning. This supports the idea that "vicarious reinforcement" might be viewed as a student misconception.

The use of multidimensional scaling plots to help pinpoint student misconceptions parallels the use of concept maps to distinguish student misconceptions (Barenholz & Tamir, 1987; Feldstine, 1987; Hoz et al., 1987). While concept maps have the advantage of not needing to be analyzed by the somewhat esoteric method of multidimensional scaling, the method outlined in this paper can be readily used to analyze the data from a group of students. Multidimensional scaling analysis also lends itself to quantitative measurement, whereas the measurement of individual student concept maps is idiosyncratic and problematic (Lay-Dopyera & Beyerbach, 1983; Stuart, 1985).

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